Investor attention and the pricing of earnings news[†]

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ABSTRACT: We investigate whether investor attention is associated with the pricing (and mispricing) of earnings news where investor attention is measured using social media activity. We find that high levels of investor attention are associated with greater sensitivity of earnings announcement returns to earnings surprises, with the effect being strongest for firms that beat analysts' forecasts. This appears to be appropriate pricing, on average, as only firms with low levels of attention are associated with significant post-earnings-announcement drift. Our results are distinct from other information sources including traditional media outlets, financial blogs, and internet search engine activity. Our results are consistent with investor attention observed in social media activity having distinct effects on the pricing and mispricing of earnings news.

Keywords: Investor Attention; Investor Sentiment; Social Media; Earnings Announcements; Capital Markets.

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1. Introduction

We investigate whether investor attention is associated with the pricing of earnings news, where investor attention is measured using social media activity. The exponential growth of social media has changed how individuals gather and share financial information by providing a platform to observe the collective attention and opinions of millions of individual investors and commentators. Our primary goal is to assess the extent to which investor attention affects the sensitivity of market prices to earnings news. Our analysis provides an initial step towards understanding whether the primary role of social media activity—a possible proxy for investor attention—is associated with more or less efficient pricing of earnings information.[1]

The level of activity on online social media platforms, such as Twitter and StockTwits, provides a measure of the attention, or interest, about the events occurring in real-time for a given stock. Twitter has over 500 million registered users, including individuals, celebrities, traditional news providers and firms.[2] These users share information by posting a 140-character or less "tweet" which is pushed to the followers of that individual and possibly "retweeted" by their followers, further extending the reach of the original posters' interests. Whether the sharing of information using online social media enhances market efficiency, however, is contentious.

On one hand, access to a vast social network facilitates the gathering and sharing of information of interest to individuals, providing an avenue through which news is instantaneously disseminated to a large audience. Shiller and Pound (1989) provide survey evidence consistent with individuals making investment decisions based on the advice of their

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[1] As we later discuss in more detail, we measure the efficiency of price responses to earnings news by the strength of the initial price reaction to earnings news at the earnings announcement coupled with an examination of post-earnings-announcement-drift to identify over- or under-reaction to the news.

[2] Blankespoor et al. (2014) investigate a sample of technology firms that use Twitter to disclose information. They find that these firms have lower bid ask spreads, consistent with firms' use of Twitter lowering information asymmetry between investors.

physical social networks, suggesting that online social networks could potentially influence investment decisions. Caskey et al. (2011) highlight in their model of information diffusion that networks potentially provide the mechanism that links the disclosure of information to the processing and pricing of that information by investors. That is, networks allow investors to become aware of new information. Social media extends the reach and spread of information through word of mouth providing widespread dissemination of new information. At the same time, investors have access to many sources of information available to them including traditional financial media, newswires, news aggregators such as Yahoo! Finance, financial blogs and message boards. Given this strong pre-existing information environment, empirical tests are required to better understand the impact of social media activity on this information environment and equity prices.

We test whether social media activity is associated with the pricing of earnings information by examining returns around, and following, earnings announcements. We measure investor attention using a recently available database of social media activity provided by Market IQ. Market IQ makes "sense of the web's most powerful real-time unstructured dataset and provides dynamic insights for today's financial professionals" (see www.themarketiq.com) using this data. Specifically, Market IQ runs patented analytics in real-time on unstructured data which appears on social networks (including Twitter and StockTwits) to provide insights into social media activity for the financial services industry. Market IQ provided us with two unique dynamic analytics, which they label "Smart Velocity" and "Smart Sentiment." We focus primarily on Smart Velocity (hereafter, *Activity*): A measure of buzz in the marketplace pertaining to a company, calculated on a continuous relative scale using Market IQ's patented algorithms. Market IQ baselines *Activity* at 1X, hence *Activity* over 1X indicates elevation of interest relative to the average level of interest for the same firm in the previous 30 days, and *Activity* below 1X reflects vice-versa. As such, Market IQ's metrics provide qualitative measures of the underlying unstructured social media data.

We focus primarily on social media activity as it may measure attentiveness and traditional asset pricing models typically assume that all investors are attentive and undertake trading actions immediately upon receipt of value relevant information. When investors have limited attention, the lower attention will lead to a lower reaction to earnings news (e.g., Hirshleifer and Teoh 2003). If investor attention varies in the cross-section, then we expect that the response to earnings news will be positively associated with the level of investor attention, and based on above, the changes in the levels of interest in a firm, or *Activity*, on the day of the earnings announcement will provide a proxy for how much increased attention investors are paying to earnings.

Using Market IQ's measure of social media activity, we find that abnormally high levels of investor attention are associated with significantly higher sensitivity of market returns to earnings news.[3] This effect is evident for both positive and negative earnings news, but the effect is much stronger for positive news. Specifically, for negative news, high levels of *Activity* are associated with approximately 91% higher sensitivity of returns to earnings news. In contrast, the sensitivity of returns to positive earnings news is approximately 234% stronger for the high *Activity* group. Firms with low levels of *Activity*, in contrast, are associated with significant post-earnings-announcement drift (*PEAD*), with no evidence of *PEAD* for portfolios

[3] To measure "earnings news" we use the median EPS forecast computed over the set of the analysts' most recent forecasts that are no earlier than two weeks before the quarterly earnings release date. This procedure avoids the problem of stale analyst forecasts. We use the unadjusted I/B/E/S forecasts to avoid losing the precision in the decimal places of the forecasts due to the I/B/E/S adjustments of prior forecasts for subsequent stock splits (Baber and Kang, 2002; Payne and Thomas, 2003). Actual earnings realizations are obtained from the unadjusted I/B/E/S actual file.

of firms with moderate to high levels of *Activity*. Our results suggest that investor attention, at least as reflected by *Activity*, is associated with an increase in the market responsiveness to earnings news and a lack of investor attention is associated with an underreaction to earnings news. Our results are not subsumed by traditional measures of attention to earnings announcements such as the market-to-book, dispersion of analysts' forecasts, size, and prior returns.

We also provide further analyses, which investigate the robustness of our findings. As high attention stocks are also likely to be growth stocks, we examine whether our results are distinct from the market-to-book (e.g. Skinner and Sloan 2002). We find evidence to suggest that social media activity is distinct from the growth stock characteristic. We next investigate Market IQ's proprietary Smart Sentiment metric (hereafter, *Sentiment*), which provides a refined measure of the relative level of optimism or pessimism observed in the discussions, or "tweets," on social networks about a company[4], Specifically, Market IQ's *Sentiment* metric takes into consideration several qualitative measures of the underlying unstructured social media data including but not limited to: contextual analysis, content propagation, and user reliability.[5] *Sentiment* is also provided on a real-time basis along with related indicators of inflection thresholds that serve as a leading indicator to potential sentiment related price movements.

Using *Sentiment*, we find that the group with the highest optimism on the day of the earnings announcement has higher market returns. We also find that *Activity* increases the sensitivity of returns to earnings for firms that announce earnings prior to the opening of the market, and decreases *PEAD*. *Activity* is lower for firms reporting after the market closes, and

[4] Sentiment is measured on a continuous scale between zero and one, which is increasing in optimism, where 0.5 is considered neutral. The sentiment measure provided is relative to the average sentiment for a given firm over the prior seven days.
[5] Market IQ is able to identify influential users within the social media networks they cover, allowing for a finer partition of the sentiment associated with news from the noise associated with social media conversations.

similar to DellaVigna and Pollet (2009) we find that *PEAD* is higher for firms that report after the market closes. Finally, our results are robust to the inclusion of information about earnings provided by traditional media outlets using the Dow Jones Newswires, financial blogs, and Google searches, suggesting that *Activity* provides a distinct proxy for attention to earnings.

We make the following contributions to the literature. First, we contribute to the recent literature on the effect of social networks on capital market outcomes. Online social networks are becoming an increasingly important part of society due to technological advancements in the past decade. We provide novel empirical evidence consistent with social media activity, as a proxy for investor attention, leading to increased sensitivity of market returns to earnings news. More broadly, our evidence complements the recent literature examining how technology aids investors in gathering information, such as via Google search (e.g., Da et al., 2010; Drake et al., 2010; Chi and Shanthikumar, 2014), and highlights that technology enables investors to also play an important dissemination role. Second, we contribute to the large body of accounting research that suggests investors underreact to earnings news (e.g., Lev, 1989; Bernard and Thomas, 1990). Prior studies have examined both the magnitude of the earnings response coefficient relative to expectations (Kormendi and Lipe, 1987) along with evidence of a post-earnings-announcement drift (e.g., Bernard and Thomas, 1989; 1990). Our evidence shows that the underreaction is concentrated in firms with the lowest levels of investor attention on the day of the earnings announcement.

2. Institutional Background and Hypothesis

2.1 Institutional background

Online social media has seen an exponential increase in activity in the past ten years. There are at least 12 social media platforms each with more than 100 million users, with over 5.7 billion (overlapping) profiles on these pages (Waite 2014). Online social networks are generally either micro-blogging websites, such as Twitter, which limit the posts to 140-character "tweets" or more traditional message board or blog-like interactions, the latter often requiring reciprocation between the individual users in the network to allow for the sharing of content. Online social networking is a recent phenomenon, with Twitter being one of the largest social networking sites. Twitter was launched on March 21st, 2006, and by 2012, broadcasted an average of 175 million "tweets" per day. Unlike other online social networks, Twitter facilitates open sharing of information through a social network as "following" another Twitter user requires no reciprocation.[6] In addition, Twitter allows for users to choose to "retweet" content they have received, allowing for information to be near instantly shared to users outside of the original audience.[7]

Historically, the primary use of data from online social networks was brand analytics, i.e., used for marketing and brand management purposes. Third-party brand analytics began as early as 2006 through Twitter which allowed for the real-time assessment of consumer thoughts and preferences. Gathering and sharing information over Twitter and similar websites has the benefit

[6] For example, social networking sites such as Facebook require that both parties agree to the social connection. Note that this feature of Twitter allows for influential users, such as Mad Money / CNBC's Jim Cramer to have significantly larger reach on Twitter, relative to other social networking sites.

[7] Kwak et al. (2010) provide a follower-following topology analysis of Twitter and find that interactions on Twitter deviate significantly from the known characteristic of human social networks. They conclude that this structure is an effective medium for the diffusion of information.

of having “hashtags” which allow for the grouping of messages by their content. Specifically, the hashtag is a metadata tag using the prefix # allowing users identify the content of their post, such as #investing to group their post into any topic area. StockTwits, an online social media platform which focuses on the sharing of information in the investment and trading community, was founded in 2008. StockTwits uses the same interface as Twitter and introduced the “cashtag” prefix, which organizes the online conversations around a company ticker, for example $AAPL identifies the stock ticker for Apple Inc.[8] StockTwits has roughly 230,000 users, relative to Twitter which has over 500 million. In July of 2012, the use of cashtags was also officially adopted by Twitter (Meredith, 2012). The cashtag feature of StockTwits allows for the identification of investors’ and other commentators’ thoughts on individual stocks in real-time.

A recent example of a social media conversation is provided in Appendix A. In this example, the cashtags link the discussion about Citigroup ($C). Some of the posts are informative, providing a hyperlink to additional material, in this case analysis of Citigroup’s earnings press release. Other comments express either a bullish or bearish opinion of the stock along with a short comment related to their position. Clearly these posts express interest by various individuals and media participants about a company’s earnings, but it is clear that the posts are also subjective and are not always in agreement.

More generally, the usefulness of the content of posts made on social media networks is contentious. On the positive side, prior to the advent of social media, Shiller and Pound (1989) survey individual investors and find that word-of-mouth suggestions influence investors’ portfolio choices, consistent with social influence affecting the portfolio choices of individual traders. As such, online social networks could act as a natural extension of the influence of

[8] Cashtags help alleviate concerns over common word ticker symbols such as “CAT” making the target of social media conversations less ambiguous than google searches.

word-of-mouth suggestions. On the negative side, in a study by Pear Analytics, Twitter conversations were analyzed over a two-week window in August of 2009, with the authors concluding that Twitter posts are 40% "Pointless babble" and 38% conversational, with the remainder being split between self-promotion, spam, pass along, and news (Ryan, 2009). In addition, commentators on Twitter highlight that "Trending topics" can often be the result of concerted efforts of users, often the fan base of certain celebrities,[9] rather than due to an event which has influenced the attention of individuals.

Whereas the use of social media is still nascent when compared to traditional news sources, such as the Dow Jones Newswire, Reuters and Bloomberg, which have a long history in financial markets, it represents an interesting intersection of finance and technology. Information from social media, however, is being used with increasing frequency in the financial services industry. High-profile investors and company executives are also increasingly using social media and the content posted by these individuals is often associated with high market volatility and investment decisions. For example, Carl Icahn an influential activist investor used his Twitter account to announce a significant purchase of Apple stock last year, this tweet was largely seen as the reason for the $17 billion increase in the market value of Apple over the following hour.[10]

In sum, social media activity provides a measure of the attention of individuals, which could potentially influence investment decisions. Whether the attention of individuals is associated with more or less efficient pricing of earnings information is an open empirical

[9] The celebrities Katy Perry and Justin Bieber have the two most followed accounts on Twitter, both with over 50 million followers. In Contrast CNN's breaking news is ranked number 32, with 16 million followers (http://twittercounter.com/pages/100) retrieved 4/27/2014.
[10] Carl Icahn's Multibillion-Dollar Tweet Boosts Apple Stock (https://finance.yahoo.com/blogs/the-exchange/carl-icahn-multibillion-dollar-tweet-boosts-apple-stock-205938760.html).

question. In the following section, we discuss how social media activity, as a proxy for investor attention might affect market efficiency.

2.2 Investor attention and the pricing of earnings

Prior literature provides a large body of evidence which suggests that investors underreact to earnings announcements. Collectively, the evidence is extensive and is based on both evidence of low responses around the date of the earnings announcements and evidence of a significant post-earnings-announcement drift following earnings announcements. Kormendi and Lipe (1987) analytically derive the expected earnings response coefficient (ERC) based on a stylized time-series model and estimate the expected ERC using estimates of the time-series properties of earnings. They find that the expected ERC for their sample is between nine and ten. They then provide empirical estimates of the ERC based on market returns and find it is approximately two to three. They find that the two ERC measures are correlated but fail to find evidence of equality. Their results suggest that the market responds in the correct direction to what is expected, but the reaction is much smaller than expected.

Ball and Brown (1968) provide initial evidence of a drift following earnings announcements. Bernard and Thomas (1989; 1990) provide evidence that this post-earnings-announcement drift is associated with an underreaction to the time-series properties of earnings. Taken together these studies suggest that investors are reacting in the correct direction to the news in earnings announcements, and that their reaction is systematically too low.

Traditional asset pricing models typically assume that 1) all investors receive publicly available information instantaneously upon its disclosure, and that 2) investors undertake trading actions immediately upon receipt of this information. That is, for an earnings announcement, when all investors pay attention to earnings announcements, these investors will react to the news in the earnings announcement by trading until the price reflects this information. When investors have limited attention, as suggested by Hirshleifer and Teoh (2003), these assumptions are unlikely to be descriptive for all stocks in the cross-section. Instead, variation in investor attentiveness is likely to be inversely related to variation in the reaction to earnings news. As abnormal social media activity on the day of the earnings announcement measures the amount of increased discussion and posts about a firm, it provides a measure of investor attention to earnings announcements. As such, we predict that high levels of investor attention will be associated with prices that are more sensitive to earnings news. As a hypothesis:

H_1: Investor attention is positively associated with the earnings response coefficient.

To test Hypothesis 1, we estimate a regression of short-run stock returns on earnings news, with the association between these variables being the measure of the earnings response coefficient (similar to the design in Easton and Zmijewski, 1989), and include an interaction term between high levels of social media activity with earnings news to identify the incremental effect of high levels of social media activity on the earnings response coefficient. In H_1, we predict that high levels of investor attention are associated with incrementally higher earnings response coefficients. Our prediction in H_1 also has implications for post earnings announcement drift. If *PEAD* is based on underreaction to earnings news, then as high levels of attention reduce the underreaction to earnings news, we expect *PEAD* to be inversely related to investor attention. As such, we expect that *PEAD* will be higher for firms with lower attention.

3. Data and Sample

3.1 Data

Market IQ provided their data to us for the period January 2012 to July 2013. In addition to other financial analytics, Market IQ provides daily measures of social media activity (*Activity*) and social media optimism (*Sentiment*). By processing millions of unstructured data streams, from social media sources, Market IQ keeps track of "investor attention" with the *Activity* metric. As activity on Social channels fluctuates, Market IQ quantifies the *Activity* metric in real-time to measure true "investor attention". As such, *Activity* is provided in the form of a multiple such as "1.50x" which would suggest that the number of mentions of the stock is 1.50 times the average level of mentions of the stock. Market IQ uses a rolling 30-day window to estimate the average level of tweets.

We obtain financial data from the Quarterly Compustat File, analyst forecasts and reported actual earnings from the I/B/E/S Unadjusted Summary File, and market data from the CRSP daily stock and index files. To be included in the sample, we require that each firm is covered by Market IQ and can be identified on Compustat, CRSP and I/B/E/S. We also require that sample firms have end of the quarter stock price of at least $5 per share. Our final sample includes 15,486 firm-quarter observations (from 2,684 unique companies).

In Figure 1, we highlight the increase in *Activity* on the days surrounding the earnings announcement. We plot *Activity* for both firms that beat the earnings forecast and those that miss the earnings forecast. On the day of the earnings announcement, firms that beat the consensus analyst forecast have an elevated amount of social media activity, at 7.028 times their base level of *Activity*. The amount of social media activity for firms that miss the consensus analyst forecast is also elevated at 5.787 times their base level of *Activity*. In a test of differences in means, we find that *Activity* for firms that beat the consensus analyst forecast is significantly higher than *Activity* for firms that miss the consensus analyst forecast (p-value for the test of differences < 0.001, untabulated). Overall, the increased level of social media activity is short-lived, as activity reverts back towards the baseline within the first two days. We also see some anticipation in the day before an earnings announcement, with elevated levels of *Activity* in day t-1. In sum, the level of social media activity increases significantly on the day of the earnings announcement.

In Figure 2, we plot the average level of optimism for firms in our sample, based on Market IQ's *Sentiment* measure. We plot *Sentiment* over the 21-day window centered on the day of the earnings announcement for firms that beat the analyst forecast and for firms that miss the analyst forecast. Figure 2 shows that the social media posts are generally optimistic, with both firms that beat the forecast and firms that miss the forecast having a level of optimism above 0.5. The level of optimism on the day before the earnings announcement is statistically higher for firms that beat their forecast (0.722) than for firms that miss (0.704), based on a p-value of less than 0.001 for the differences (not tabulated). The level of optimism drops statistically for firms that miss the analyst forecast (p-value of less than 0.001) but, on average, remains optimistic at 0.674. In sum, social media posts are generally optimistic, but are significantly less optimistic for firms that miss the earnings benchmark.

3.2 Descriptive statistics

In Table 1, we provide descriptive statistics of our dependent and independent variables along with control variables. We report the averages for all firms in the sample as well as for each quintile based on the level of social media activity on the day of the earnings announcement. The average level of *Activity* on the day of the earnings announcement for all firms in the sample is 6.429 (column 1). The average of the lowest group is 0.126 and the average of the highest group is 19.335. These results suggest that there is significant variation in *Activity* on the day of the earnings announcement across the firms in the sample.

We find that the variation in *Activity* is associated with the return on the day of the earnings announcement, *CAR*, with the lowest *Activity* group having an average *CAR* of -0.1% whereas the average returns among the highest *Activity* group is 0.7% with the difference being statistically significant (p-value < 0.001); we will condition on the magnitude of the earnings news in the next table as well as in our multivariate analysis. We also find evidence of a statistically significant difference (p-value < 0.05) in *PEAD* between the highest and lowest activity groups; firms in the lowest social media activity group display higher returns of 0.8% (column 2) relative to firms in the highest social media activity group, which display returns of 0.1% (column 6). We also report higher positive forecast errors (*%Good*) for the firms in the highest activity group relative to those in the lowest activity group, with similar results for the proportion of firms beating the analyst forecast (p-value < 0.001), consistent with individual traders preference for taking long positions at earnings announcements (Hirshleifer et al., 2008). Sentiment is higher for the lower activity stocks suggesting lower levels of optimism for stocks with the largest amount of activity (p-value < 0.01).

Social media activity on the day of the earnings announcement is also positively associated with analyst following and the number of analyst forecasts. The standard deviation of analysts' forecasts is smaller for firms with the highest activity relative to the lowest activity (p-value < 0.05). We also find that higher activity stocks are higher momentum stocks, are larger in size (p-value < 0.01), and have a higher market-to-book ratio (p-value < 0.001), on average. We also find that firms with earnings announcements prior to the market open have a higher level of *Activity* (*p*-value < 0.001).

3.3 Market returns around earnings announcements

We next provide descriptive evidence on whether market returns are more sensitive to earnings news when investor attention is higher. In Table 2 we present the mean cumulative abnormal return sorted by forecast error quintiles in rows and by *Activity* quintiles in columns. Where *CAR* is cumulative abnormal returns surrounding the window of the earnings announcement [0,+1], based on the firms return less the return on the firm's size decile, *Ferror* is the forecast error scaled by the price at the end of the quarter and *Activity* is Market IQ's velocity measure sorted into quintiles by year and quarter. In column 1, we document the well-observed positive association between *Ferror* and *CAR*. As expected, the most negative forecast errors are associated with negative returns (average = -3.3%), while the most positive forecast errors are associated with positive returns (average = 3.1%) and this difference is statistically significant (p-value < 0.001).

Within each of the *Activity* groups, we find that the differences between the highest and lowest forecast errors are U-shaped. These results are documented in the row labelled FE5-FE1. For example, the average difference in *CAR* for the low activity group (Q1) is 6.0% versus 4.6% for the median group (Q3) and 10.4% for the highest attention group (Q5). In all cases, however, the differences are positive and significant as expected. The sorts by social media activity highlight that social media activity matters for both the most positive and most negative earnings surprises. For example, the average *CAR* for the most negative earnings surprises for the low activity group is -3.1% versus -5.1% for the highest attention group (p-value < 0.001). Similarly, for the most positive earnings surprises, the average *CAR* is 2.9% for the lowest activity group and 5.3% for the highest activity group (p-value < 0.001).

These results provide some descriptive evidence in support of Hypothesis 1. Specifically, within forecast error deciles, social media activity matters most for the extreme deciles. We next provide descriptive evidence on whether social media activity is associated with *PEAD*.

3.3 Market returns subsequent to earnings announcements

Prior literature provides evidence that *PEAD* has been declining over time (Chordia et al. 2009). In Table 3, Column 1, we report the cumulative returns over 58 days (from day t+2 to day t+60) following the earnings announcement for the full sample. Based on the difference between the highest and lowest earnings surprise groups, we find marginal evidence of a difference in PEAD (p-value < 0.10). In Column 2, however, we report evidence of *PEAD* within the firms with the lowest level of *Activity*. In this case, the portfolio with the lowest earnings surprises underperforms the group with the highest earnings surprises by 2.6% or approximately 57% of the original earnings response (6.0% in Column 1 of Table 2).

We do not find statistically significant evidence of *PEAD* in any of the other social media groupings (Columns 3-6). In Column 7, we report the differences between the highest and lowest activity portfolios within each forecast error grouping. In general, the results do not provide compelling evidence of a difference in *PEAD* within each forecast error grouping, although we find some evidence of differences within the middle and top forecast error quintiles, which is driven primarily by the positive returns in the lowest activity group.

In sum, our descriptive analysis of *PEAD* suggests that *PEAD* is only observed in the lowest activity quintile, consistent with Hirshleifer and Teoh (2003), suggesting that firms with moderate to high levels of social media activity on average have no evidence of *PEAD* in our sample period.

4. Multivariate analysis

4.1 Tests of Hypothesis 1

To test our first hypothesis, we first examine whether increased investor attention increases the sensitivity of market returns to earnings news. Specifically, we estimate the association between earnings news and market returns by estimating a regression of short-window returns around the earnings announcement on the consensus analyst forecast error divided by stock price at the end of the quarter ($Ferror_q$). As negative earnings news is expected to have a differential response, we separate positive and negative earnings surprises (e.g. Skinner and Sloan, 2002). Our independent variable of interest is the interaction between an indicator variable for the highest level of *Activity* (*HiAct*) and the scaled forecast error (*Ferror*).

According to Hypothesis 1, we predict that the interaction will be positive and significant. We also include control variables for other firm characteristics which could be correlated with both our variable of interest and the market response; size, market-to-book, momentum, analyst dispersion, and leverage. Specifically we estimate the following regression:

$$CAR_q = a_0 + b_1 Ferror_q^+ + b_2 Ferror_q^- + b_3 HiAct_q + b_4\, Ferror_q^+ \times HiAct_q + b_5\, Ferror_q^- \times HiAct_q + controls_q \qquad (1)$$

Where CAR_q is the two-day cumulative abnormal returns to the quarter q earnings announcement on the day of and day following the announcement (i.e., over the window [0,+1]), based on the firm's return less the return on the firm's size decile, $Ferror_q^+$ is the positive forecast error scaled by the price at the end of the quarter, and zero otherwise, $Ferror_q^-$ is the negative forecast error scaled by the price at the end of the quarter, and zero otherwise, $HiAct_q$ is an indicator variable set to one for observations in the highest quintile of *Activity* sorted by year and quarter, and zero otherwise. Our prediction is that b_4 and b_5 will be positive and significant.

We also include the following controls: *LoAct* is an indicator for the lowest quintile of social media activity, which we also interact with positive and negative forecast errors, *Size* is the log of total assets, *M/B* is the market-to-book ratio, which we also interact with the positive and negative forecast errors based on Skinner and Sloan (2002), σAF is the standard deviation of analyst forecasts, *Mom* is stock return momentum in the month before the earnings announcement, and *Leverage* is the firm's debt-to-asset ratio.

We report the results of this regression in Columns 1 and 2 of Table 4. In the first column, we present results for a restricted model which excludes control variables. Consistent with prior research, we find that the coefficient on the analyst forecast error is positive and highly significant for both positive (b_1 = 1.912, p<0.001) and negative earnings surprises (b_2 = 1.514, p<0.001). Consistent with our main prediction, we find evidence of a significant positive association between social media activity on the day of the earnings announcement and the sensitivity of market prices to positive earnings news (b_4 = 4.469, p<0.001) and negative earnings news (b_5 = 1.371, p<0.05). The incremental effect of high levels of social media activity on the sensitivity of earnings news is much stronger for positive earnings news at approximately 234% (4.469/1.912) versus 90.6% (1.371/1.514).[11]

In Column 2, we report the model including control variables and find that the effects of high levels of social media activity are not subsumed by other firm characteristics. When

[11] Fischer et al. (2014) provide a model of exaggerated earnings sensitivity where rational investors trade heavily on earnings news in the expectation that future investors will do so as well. The much higher coefficient on the interaction of attention and positive earnings surprises could be a rational response to expected future attention being higher for current attention to good news.

including controls, we find that the interactions between *LoAct* and *Ferror*$^{+}$ is positive and significant, however, the economic magnitude of the results are much smaller than for the high activity interactions. In sum, our results provide support for Hypothesis 1, that increased investor attention is associated with market prices which are more sensitive to earnings.

In Column 3, we report the association between returns following the earnings announcement over the period [+2, +60] and the interactions between social media activity and forecast errors. Based on Hypothesis 1, if investor attention increases the reaction to earnings news on the day of the earnings announcement, we expect less underreaction to earnings news in the period after the announcement. As such, we expect that post earnings returns will only be associated with earnings surprises for firms with low levels of *Activity*. Consistent with Hypothesis 1, we find evidence consistent with this prediction for both the positive and negative earnings surprise groups.

5. Further Analysis

5.1 Social media activity and growth stocks

Skinner and Sloan (2002) show that the sensitivity of market returns to earnings news is more sensitive to growth firms relative to value firms; in this section we reconcile with their findings and identify that social media activity is incremental to their sort on growth. This analysis is important as it is possible that growth firms are more actively followed on Twitter.

Figure 3 plots the cumulative abnormal returns (*CAR*) surrounding the two-day window of the earnings announcement [0,+1] for high attention and high growth stocks as a function of the quarterly earnings forecast error. In Figure 3, the returns to high activity firms, which are those firms in the highest quintile based on Market IQ's velocity measure on the day of the earnings announcement, are more sensitive to earnings news than the growth firms, which are those firms in the highest quintile sorted on market-to-book ratios.

Models of investor sentiment, such as Shiller (1984) and DeLong et al. (1990), predict that investors do not optimally trade on fundamental information but rather on "sentiment" or "fads." If investors are on average overly optimistic, then sentiment trading may dampen the effect of earnings news. We use Market IQ's sentiment measure to investigate this possibility.[12] In Table 5, we examine the relation between high levels of *Activity* and *Sentiment* and the quarterly return (*Fullret*). In this section, we follow Skinner and Sloan (2002) and use the entire quarter return due to the possibility of bad news being pre-announced. In Column (1), we find the interactions of *HiAct* and $Ferror^{+}$ and *HiAct* and $Ferror^{-}$ are both positive and significant. In Column (2), we examine how investor sentiment influences the relation between earnings news and *Fullret*. We find *HiSent* is positively related to *Fullret*, suggesting that *HiSent* firms have positive quarterly returns on average.[13] We also find the interaction between *HiSent* and $Ferror^{-}$ is negative and significant, which suggests that firms with high investor sentiment at the earnings announcement and miss analyst earnings expectations, have less negative abnormal returns. In Column (3), we continue to find the interactions of *HiAct* and $Ferror^{+}$ and *HiAct* and $Ferror^{-}$ to be positive and significant. We also continue to find a positive relation between *HiSent* and *Fullret* and a negative relation between the interaction of *HiSent* and $Ferror^{-}$ and *Fullret*. These results are consistent with a dampened response to negative earnings news due to investor optimism.[14]

[12] Note that not all firms have available data on sentiment we exclude those with missing values from this analysis.
[13] Similar results are found at the time of the earnings announcement using the short-window returns in Table 4. We leave to future research whether this effect is due to sentimental investors "ignoring" earnings warnings and other negative news prior to the earnings announcement, or for some other reason.
[14] Our results are consistent with Burger and Curtis (2014) who provide evidence of the increase in margin debt in recent years being associated with a lower sensitivity of aggregate prices to aggregate accounting fundamentals.

5.2 Robustness to earnings announcement timing

Patell and Wolfson (1982) document that announcements made after the market close tend to have negative earnings news. DellaVigna and Pollet (2009) suggest that timing is associated with variation in investor attention. We find that social media activity appears to have different effects based on whether the firm announces prior to the market open or after the market closes.[15] In Table 6, we report evidence suggesting the effects social media activity is higher for the firms reporting prior to the market opening than for firms reporting after the market closes. We observe a significant interaction effect between positive forecast errors and social media activity for firms reporting before the market opens. We also find that the effects of low activity on *PEAD* are observed for firms announcing positive or negative earnings news after the market.

5.3 Robustness to other information intermediaries

In Table 7, Panels A and B, we document that our primary results are robust to the inclusion of information about earnings provided by traditional media outlets using the Dow Jones Newswires, financial blogs, and Google searches, suggesting that social media activity provides a distinct proxy for attention to earnings. Li et al. (2011) find that traditional newswires enhance the market pricing of value relevant information in SEC filings and Da et al. (2011) highlight that investor demand for information can be gathered from Google search trends. Finally, Drake et al. (2012) find that when investors perform more Google searches in the days prior to the earnings announcement there is a lower price reaction when earnings are announced

[15] We leave day of the week effects to future research. Doyle and Magilke (2009) and DeHaan et al. (2014) provide evidence on the effect of announcing earnings on Fridays versus other days of the week.

and Chi and Shanthikumar (2014) document that contemporaneous Google search is associated with an increase in the market's response to earnings news, which is higher when the individuals searching are geographically dispersed. As such, we investigate the robustness of social media activity to the inclusion of these traditional proxies for the information environment.

In Table 7 Panel A, In Column (1), after controlling for investor demand for information through Google searches, we find a larger market reaction to positive and negative earnings news when there are high levels of social media activity (*HiAct*). We also find a larger market reaction to positive news when there are low levels of social media activity (*LoAct*). However, we do not find evidence of an association between the earnings response coefficient and Google searches prior to the earnings announcement.[16]

In Column (2), after controlling for information from other sources (i.e., blogs and the Dow Jones Newswire), we continue to find a larger market response to positive earnings news in the presence of high and low levels of social media activity and for negative earnings news in the presence of low levels of social media activity. We also find that increased coverage of the earnings announcement through the Dow Jones Newswire leads to increased sensitivity of market returns to negative earnings information. In Column 3, after including both Google searches and other sources of information, we continue to find a larger market response to positive earnings in the presence of high and low social media activity.

In Table 7 Panel B, we examine the relation between attention and *PEAD* after controlling for alternative sources of online information. In Column (1), we find a negative

[16] To perform this test, we use weekly google search data as this is the highest frequency data available during our sample period and limit the sample to observations where the end of the google search period is within seven days of the earnings announcement. Additionally, the sample size is small because we are only able to obtain google search data for 2012 and the data excludes many companies with ticker symbols that are also common words (e.g., CAT). As such the results should be interpreted with these caveats and is not directly comparable to daily google search data used in Drake et al. (2012).

relation between low levels of social media activity (*LoAct*) and *PEAD* after controlling for Google searches. In Column (2), we do not find a significant relation between social media activity and *PEAD* after controlling for news from traditional media outlets. However, in Column (3), we find *LoAct* negatively related to *PEAD* and the interaction between $Ferror^+$ and *LoAct* positively related to *PEAD* after controlling for both Google searches and news from traditional media outlets.

5.4 Caveats

Our results should be interpreted with the important caveat that our data span is short – we are only able to measure social media activity over the period January 2012 through July 2013. In part, this is due to the nature of social media networks which have only recently experienced significant growth. For example, GNIP (2014) reports that “cashtagging” – the way in which investors communicate the ticker symbol of the company – have increased 550% between 2011 and 2014. Additionally, it is important to note that even regulatory bodies such as the SEC have recently embraced the use of social media channels to broadcast market-moving corporate news, which will potentially result in continued high levels of growth in the use of social media by firms and investors over time. Hence, our results should be considered as providing preliminary evidence on the role of social networks on the pricing of earnings news. Our results are also limited to periods which are out-of-sample to the prior literature, which provides many of the predictions which we test. In some senses this caveat is also a strength of the findings, as our time period shares many empirical regularities highlighted by the prior literature.

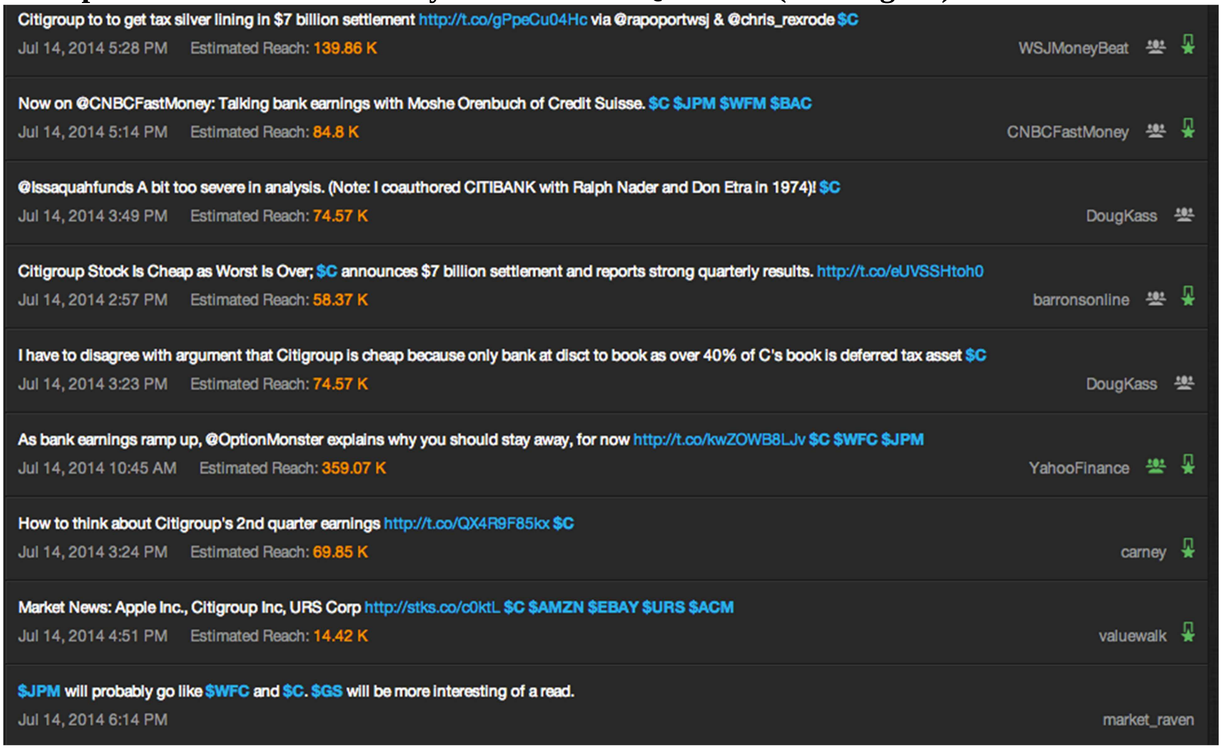
6. Conclusion

The purpose of this paper is to investigate whether investor attention through online social media networks is associated with the pricing, and mispricing, of earnings news. Social media is a relatively new feature of financial markets, which has become an increasingly large channel through which the discussions and preferences of individuals can be measured. We focus primarily on the role of social media activity, which we predict will be associated with an increase in the sensitivity of market returns to earnings news. We find that a firm's social media activity increases significantly on the day of the earnings announcement for firms with positive and negative earnings news.

We find evidence in support of our hypothesis – the prediction that high levels of abnormal social media activity are associated with increased sensitivity of earnings announcement returns to earnings surprises. The effects associated with increased social media activity are greatest for firms that beat analysts' forecasts. We also document evidence of a significant post-earnings-announcement drift for the portfolio of firms with the lowest levels of social media attention to earnings announcements. Our results are based on a direct proxy for investor attention and are consistent with investor attention to earnings announcements being inversely associated with the underreaction to earnings news.

Our results are incremental to, and larger than, the value-growth partition, and are robust to the timing of earnings announcements and to the inclusion of additional online information proxies. Our results provide implications for future research, especially research that examines variation in investor attention and investor sentiment. Specifically, social media appears to provide observable proxies for these theoretical constructs.

Appendix A
Example of Social media Activity from MarketIQ for Citi (Cashtag $C)


Citigroup to to get tax silver lining in $7 billion settlement http://t.co/gPpeCu04Hc via @rapoportwsj & @chris_rexrode $C
Jul 14, 2014 5:28 PM Estimated Reach: 139.86 K WSJMoneyBeat

Now on @CNBCFastMoney: Talking bank earnings with Moshe Orenbuch of Credit Suisse. $C $JPM $WFM $BAC
Jul 14, 2014 5:14 PM Estimated Reach: 84.8 K CNBCFastMoney

@issaquahfunds A bit too severe in analysis. (Note: I coauthored CITIBANK with Ralph Nader and Don Etra in 1974)! $C
Jul 14, 2014 3:49 PM Estimated Reach: 74.57 K DougKass

Citigroup Stock Is Cheap as Worst Is Over; $C announces $7 billion settlement and reports strong quarterly results. http://t.co/eUVSSHtoh0
Jul 14, 2014 2:57 PM Estimated Reach: 58.37 K barronsonline

I have to disagree with argument that Citigroup is cheap because only bank at disct to book as over 40% of C's book is deferred tax asset $C
Jul 14, 2014 3:23 PM Estimated Reach: 74.57 K DougKass

As bank earnings ramp up, @OptionMonster explains why you should stay away, for now http://t.co/kwZOWB8LJv $C $WFC $JPM
Jul 14, 2014 10:45 AM Estimated Reach: 359.07 K YahooFinance

How to think about Citigroup's 2nd quarter earnings http://t.co/QX4R9F85kx $C
Jul 14, 2014 3:24 PM Estimated Reach: 69.85 K carney

Market News: Apple Inc., Citigroup Inc, URS Corp http://stks.co/c0ktL $C $AMZN $EBAY $URS $ACM
Jul 14, 2014 4:51 PM Estimated Reach: 14.42 K valuewalk

$JPM will probably go like $WFC and $C. $GS will be more interesting of a read.
Jul 14, 2014 6:14 PM market_raven

Notes: The above figure displays a typical social media conversation reported on MarketIQ's social media feed about an earnings announcement. The above was collected from MarketIQ. Retrieved 7/16/2014.

Appendix B
Variable Definitions

Variable Name	Description
Activity	Measure of social media activity from Market IQ, where 1x is the baseline effect that is measured over a 30 day rolling window;
HiAct	An indicator variable set to one for the highest quintile of social media activity, zero otherwise;
LoAct	An indicator variable set to one for the lowest quintile of social media activity, zero otherwise;
$Ferror^{+}$	Positive forecast error, scaled by end of the quarter price. Measured as the actual earnings realization from the I/B/E/S unadjusted actuals file minus the median analyst consensus forecast from the I/B/E/S unadjusted summary file;
$Ferror^{-}$	Negative forecast error, scaled by end of the quarter price. Measured as the actual earnings realization from the I/B/E/S unadjusted actuals file minus the median analyst consensus forecast from the I/B/E/S unadjusted summary file;
%Good	The percentage of observations that report earnings that beat the median analyst consensus;
Sentiment	Measure of firms-specific investor social media sentiment from Market IQ, measured as a seven day rolling average;
HiSent	An indicator variable set to one for the highest quintile of social media sentiment, zero otherwise;
LoSent	An indicator variable set to one for the lowest quintile of social media sentiment, zero otherwise;
CAR	Cumulative abnormal returns, measured as the firm's return less the return on the firm's size decile over the two-day window surrounding the earnings announcement [0,+1];
PEAD	Post earnings announcement drift, measured as the firm's return less the return on the firm's size decile over the window [+2,+60] relative to the earnings announcement;
Fullret	The quarterly return, measured as the firm's buy and hold return less the return on the firm's size decile over the period starting 2 days after the previous quarter's earnings announcement to 1 day after the current quarter's earnings announcement;
M/B	Market-to-book, measured as the market value of equity divided by common equity at the end of the quarter;

%Pre-open	The percentage of firms reporting earnings before the market opens;
Pre-AbSearch	Abnormal Google SVI in the week before the earnings announcement;
Size	The natural log of total assets;
Mom	Momentum, measured as the firm's buy and hold return in the month prior to the earnings announcement;
σAF	The standard deviation of analyst forecasts, taken from the I/B/E/S unadjusted summary file;
#Forecasts	The number of analysts issuing forecasts, taken from the I/B/E/S unadjusted summary file;
HiDJN	Indicator variable set to one if the number of Dow Jones Newswire articles on the day of the earnings announcement is greater than the sample median, zero otherwise;
HiBlog	Indicator variable set to one if the number of blog posts on the day of the earnings announcement is greater than the sample median, zero otherwise;
Leverage	The ratio of long-term debt to total assets.

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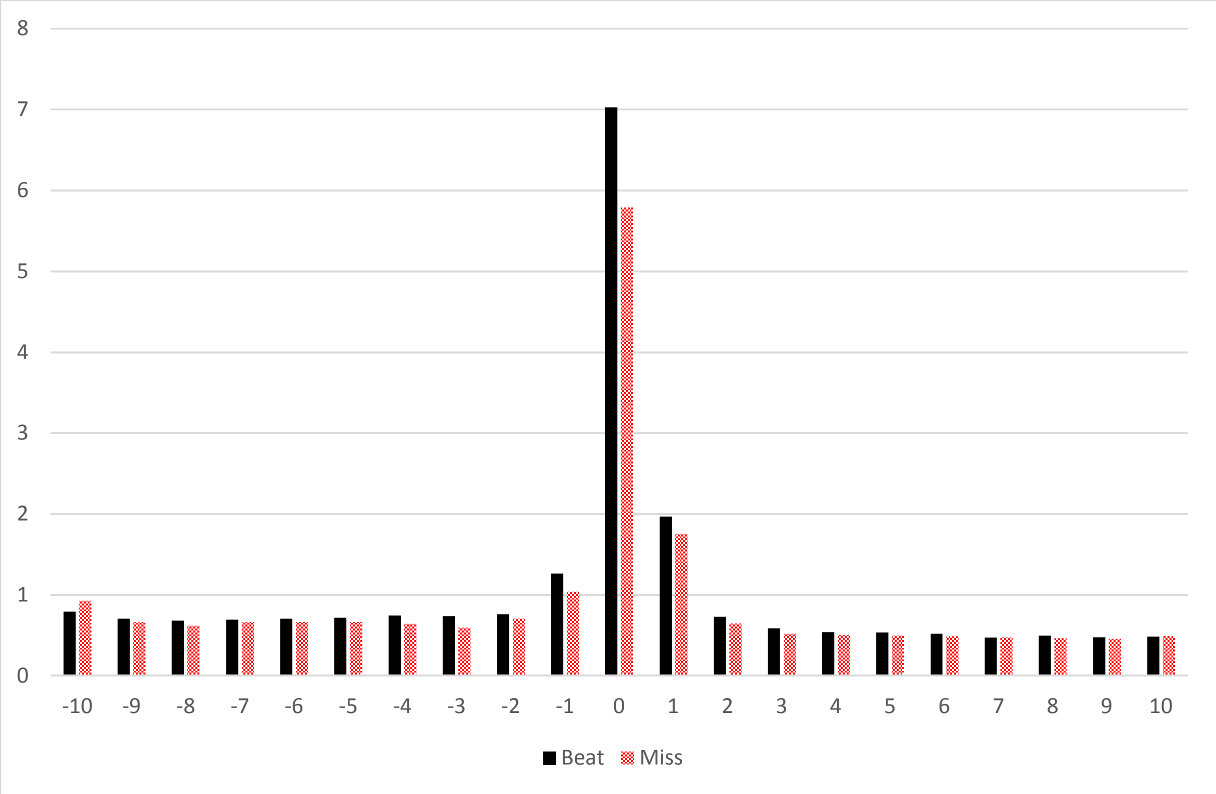
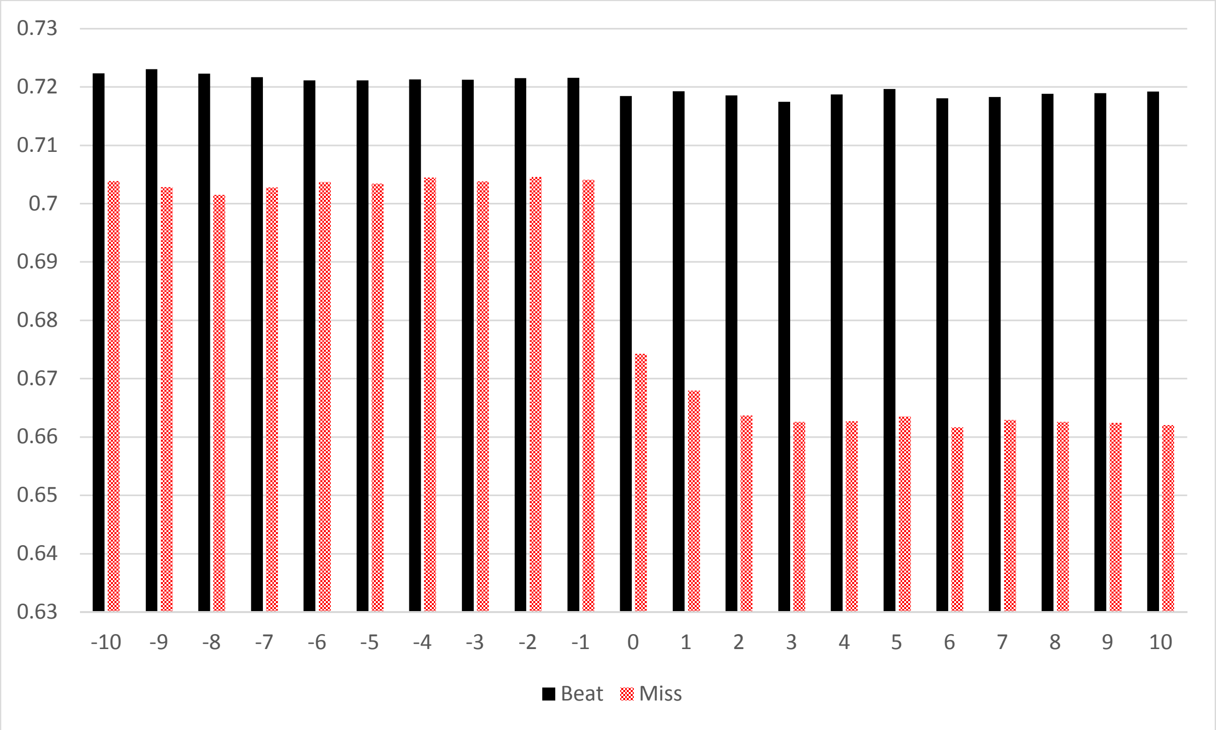
Figure 1
Social media activity around earnings announcements



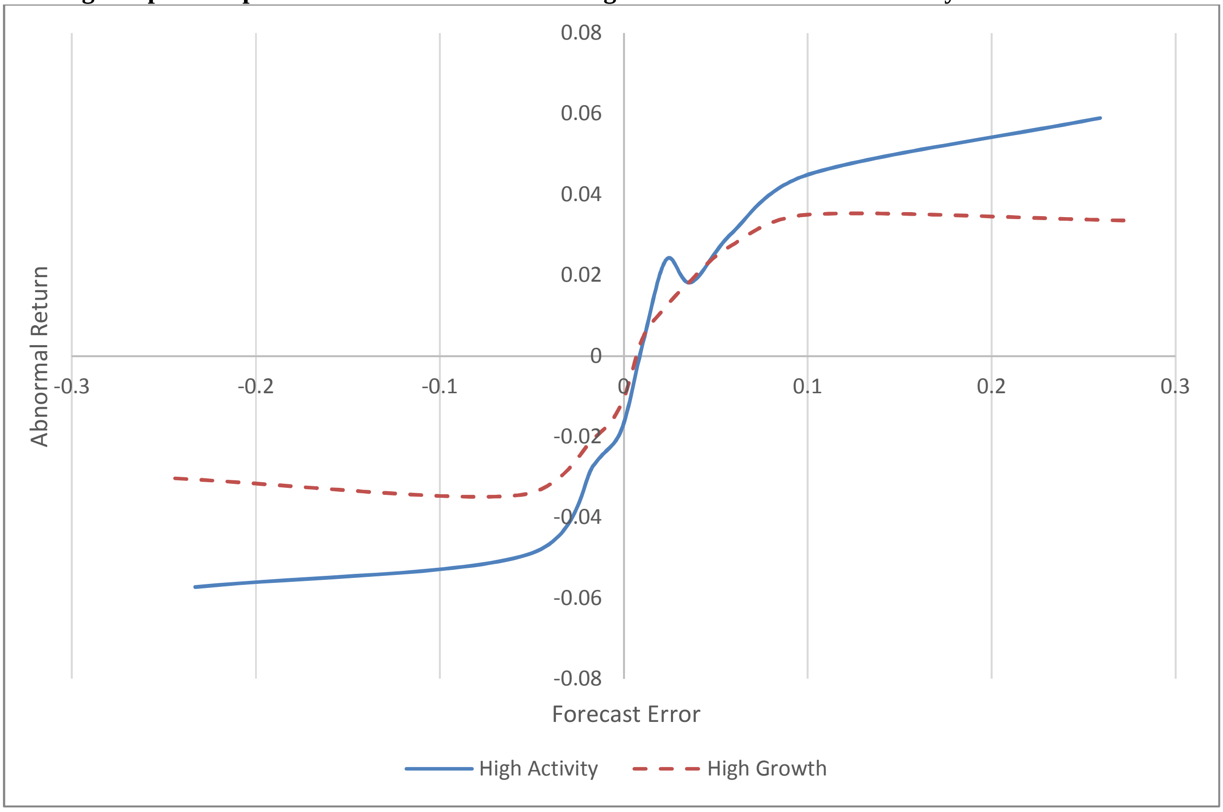
Notes: This graph displays social media activity using Market IQ's velocity measure in the 21-day window surrounding the earnings announcements firms that beat the consensus analyst forecast are displayed as the solid bars, and firms that miss the consensus analyst forecast are displayed as the shaded bars.

Figure 2
Social media optimism around earnings announcements



Notes: This graph displays social media optimism using Market IQ's sentiment measure in the 21-day window surrounding the earnings announcements. Firms that beat the consensus analyst forecast are displayed as the solid bars, and firms that miss the consensus analyst forecast are displayed as the shaded bars.

Figure 3
Earnings surprise response functions for firms with high levels of social media activity



Notes: This figure plots cumulative abnormal returns (*CAR*) surrounding the two-day window of the earnings announcement [0,+1] for high attention and high growth stocks as a function of the quarterly earnings forecast error. The solid line represents high activity firms, which are those firms in the highest quintile based on Market IQ's velocity measure on the day of the earnings announcement. The dashed line represents growth firms, which are those firms in the highest quintile sorted on market-to-book ratios. Each plot is formed by dividing the stocks into ten portfolios based on the magnitude of the forecast error, and then plotting the mean portfolio abnormal returns and forecast errors. The resulting points are connected for illustrative purposes.

Table 1

Means of earnings news and market returns sorted by social media activity

Variable	Full Sample	Q1	Q2	Q3	Q4	Q5	Q5-Q1	*t*-test	p-value
Activity	6.429	0.126	1.926	3.770	7.331	19.335			
Ferror	0.018	0.011	0.010	0.016	0.024	0.029	0.019	5.617	0.000
%Good	0.587	0.543	0.547	0.571	0.620	0.655	0.112	9.360	0.000
Sentiment	0.705	0.712	0.712	0.711	0.706	0.691	-0.020	-2.882	0.004
CAR	0.001	-0.001	-0.003	0.000	0.002	0.007	0.008	4.048	0.000
PEAD	0.005	0.008	0.006	0.005	0.007	0.001	-0.007	-2.163	0.031
Fullret	0.011	0.007	0.015	0.009	0.011	0.014	0.007	1.769	0.007
M/B	2.945	2.309	2.921	2.947	3.136	3.526	1.217	13.796	0.000
%Pre-open	0.454	0.358	0.334	0.439	0.545	0.590	0.232	18.688	0.000
Size	9,959.089	3,027.993	6,834.664	9,963.548	14,430.430	16,249.520	13,221.520	20.784	0.000
Mom	0.017	0.010	0.018	0.020	0.020	0.016	0.006	2.926	0.003
σAF	0.045	0.043	0.050	0.047	0.045	0.039	-0.003	-2.362	0.018
#Forecasts	10.104	6.102	9.154	10.388	11.780	13.661	7.559	49.321	0.000
Leverage	0.199	0.175	0.223	0.219	0.205	0.183	0.007	1.615	0.106

Notes: *Activity* is Market IQ's velocity measure, where 1x is the baseline effect, *CAR* is cumulative abnormal returns surrounding the window of the earnings announcement [0,+1], based on the firm's return less the return on the firm's size decile, *Ferror* is the forecast error scaled by the price at the end of the quarter, *HiAct* is an indicator variable set to one for observations in the highest decile of investor social media activity on the day of the earnings announcement (*Activity*) sorted by year and quarter, and zero otherwise, *Size* is the log of total assets, *M/B* is the market-to-book ratio, *σAF* is the standard deviation of analyst forecasts, *Mom* is stock return momentum in the month before the earnings announcement.
*** p<0.010, ** p<0.050, * p<0.10

Table 2

CAR sorted by forecast error and social media activity

Variable	(1) Full Sample	(2) Q1	(3) Q2	(4) Q3	(5) Q4	(6) Q5	(7) Q5-Q1	t-test	p-value
FE1	-0.033	-0.031	-0.028	-0.022	-0.034	-0.051	-0.020	-5.080	0.000
FE2	-0.014	-0.013	-0.013	-0.014	-0.008	-0.022	-0.008	-2.152	0.032
FE3	0.006	0.006	0.005	0.003	0.005	0.012	0.006	1.642	0.101
FE4	0.019	0.019	0.008	0.017	0.024	0.026	0.007	1.793	0.075
FE5	0.031	0.029	0.018	0.024	0.030	0.053	0.024	5.317	0.000
FE5-FE1	0.065	0.060	0.046	0.046	0.065	0.104	0.084		
t-stat	35.437	19.690	11.873	11.795	16.943	19.334		19.725	
P-value	0.000	0.000	0.000	0.000	0.000	0.000			0.000

Note: FE1 through FE5 represents quintiles of *Ferror*, with FE1 representing firms with the lowest *Ferror* and FE5 representing firms with the highest *Ferror*. Q1 through Q5 represent quintiles of *Activity*, with Q1 representing the lowest level of *Activity* and Q5 representing the highest level of *Activity*. We perform this double sort by ranking *CAR* by *Ferror* quintile and within each *Ferror* quintile we perform a quintile rank by *Activity*.

Table 3

Post-earnings announcement returns sorted by forecast error and social media activity

Variable	(1) Full Sample	(2) Q1	(3) Q2	(4) Q3	(5) Q4	(6) Q5	(7) Q5-Q1	t-test	p-value
FE1	0.003	-0.005	0.015	0.008	0.002	0.002	0.007	0.891	0.373
FE2	0.000	0.001	-0.002	0.004	0.002	-0.005	-0.006	-0.841	0.400
FE3	0.007	0.015	0.001	0.006	0.009	0.004	-0.011	-1.701	0.089
FE4	0.007	0.012	0.013	0.001	0.008	0.003	-0.009	-1.224	0.221
FE5	0.009	0.021	0.008	0.005	0.010	0.002	-0.019	-2.635	0.009
FE5-FE1	0.006	0.026	-0.007	-0.003	0.008	0.000	0.007		
t-stat	1.683	3.692	-0.730	-0.316	0.920	0.015		0.9436	
p-value	0.092	0.000	0.466	0.752	0.358	0.988			0.346

Note: FE1 through FE5 represents quintiles of *Ferror*, with FE1 representing firms with the lowest *Ferror* and FE5 representing firms with the highest *Ferror*. Q1 through Q5 represent quintiles of *Activity*, with Q1 representing the lowest level of *Activity* and Q5 representing the highest level of *Activity*. We perform this double sort by ranking *PEAD* by *Ferror* quintile and within each *Ferror* quintile we perform a quintile rank by *Activity*.

Table 4
Multivariate tests with *CAR* and *PEAD*

	(1) *CAR*			(2) *CAR*			(3) *PEAD*		
	coef	**p-value**		**coef**	**p-value**		**coef**	**p-value**	
Intercept	-0.002	0.047	**	0.001	0.730		0.001	0.886	
$Ferror^{+}$	1.912	0.000	***	1.573	0.000	***	1.015	0.150	
$Ferror^{-}$	1.514	0.000	***	1.151	0.000	***	-0.753	0.093	*
HiAct	-0.000	0.935		-0.001	0.782		-0.006	0.051	*
$Ferror^{+}$ *x HiAct*	4.469	0.000	***	4.658	0.000	***	0.645	0.556	
$Ferror^{-}$ *x HiAct*	1.371	0.017	**	1.455	0.012	**	-0.798	0.509	
LoAct				-0.002	0.232		0.001	0.725	
$Ferror^{+}$ *x LoAct*				0.958	0.062	*	1.532	0.045	**
$Ferror^{-}$ *x LoAct*				0.294	0.273		1.248	0.060	*
M/B				0.000	0.007	***	0.001	0.128	
$Ferror^{+}$ *x M/B*				0.145	0.363		-0.431	0.141	
$Ferror^{-}$ *x M/B*				0.196	0.111		0.380	0.100	
Size				-0.001	0.157		-0.000	0.964	
σAF				-0.015	0.214		0.008	0.755	
Mom				0.007	0.411		-0.029	0.109	
Leverage				0.004	0.197		0.011	0.067	*
Number of observations	15,468			15,468			15,468		
Adjusted R^2	0.073			0.075			0.004		

Note: Please see Appendix B for variable definitions, *** p<0.010, ** p<0.050, * p<0.10

Table 5
Multivariate tests of Fullret with Attention and Investor Sentiment

	(1) FULLRET			**(2) FULLRET**			**(3) FULLRET**		
	coef	**p-value**		**coef**	**p-value**		**coef**	**p-value**	
Intercept	0.013	0.101		0.012	0.254		0.009	0.370	
Ferror^{+}	2.392	0.000	***	2.280	0.004	***	1.485	0.024	**
Ferror^{-}	1.642	0.005	***	2.434	0.000	***	2.222	0.000	***
HiAct	-0.002	0.636					-0.002	0.719	
Ferror^{+} *x HiAct*	4.644	0.011	**				4.487	0.028	**
Ferror^{-} *x HiAct*	2.070	0.016	**				1.950	0.036	**
LoAct	-0.001	0.663					0.008	0.280	
Ferror^{+} *x LoAct*	1.341	0.132					1.317	0.581	
Ferror^{-} *x LoAct*	-0.345	0.604					-0.307	0.736	
HiSent				0.032	0.000	***	0.031	0.000	***
Ferror^{+} *x HiSent*				-0.487	0.722		-0.068	0.952	
Ferror^{-} *x HiSent*				-1.614	0.018	**	-1.428	0.043	**
M/B	0.003	0.000	***	0.003	0.000	***	0.003	0.000	***
Ferror^{+} *x M/B*	0.266	0.440		0.816	0.124		0.637	0.231	
Ferror^{-} *x M/B*	0.165	0.516		0.138	0.630		0.091	0.766	
Size	-0.004	0.000	***	-0.004	0.000	***	-0.004	0.000	***
sAF	-0.001	0.967		0.003	0.936		0.000	0.994	
Leverage	0.009	0.169		0.001	0.867		0.003	0.767	
Number of observations	15,363			9,932			9,932		
Adjusted R^2	0.203			0.201			0.204		

Note: Please see Appendix B for variable definitions, *** p<0.010, ** p<0.050, * p<0.10

Table 6
Pre-open versus post-close announcements

	CAR						PEAD					
	(1) Pre-Open			**(2) Post-Close**			**(3) Pre-Open**			**(4) Post-Close**		
	coef	**p-value**		**coef**	**p-value**		**coef**	**p-value**		**coef**	**p-value**	
Intercept	-0.000	0.976		-0.003	0.623		-0.010	0.407		0.008	0.411	
$Ferror^+$	1.021	0.012	**	2.156	0.000	***	1.198	0.302		0.791	0.213	
$Ferror^-$	0.797	0.043	**	1.337	0.000	***	-2.007	0.009	***	-0.652	0.289	
HiAct	-0.002	0.521		-0.002	0.570		-0.007	0.091	*	-0.010	0.092	*
$Ferror^+$ *x HiAct*	7.011	0.000	***	2.089	0.116		1.570	0.251		0.441	0.775	
$Ferror^-$ *x HiAct*	1.795	0.002	***	1.406	0.234		-1.067	0.516		0.227	0.864	
LoAct	-0.000	0.925		-0.003	0.222		0.007	0.194		-0.002	0.592	
$Ferror^+$ *x LoAct*	1.219	0.132		0.474	0.472		0.140	0.898		3.480	0.000	***
$Ferror^-$ *x LoAct*	0.467	0.276		0.046	0.919		1.566	0.137		2.032	0.027	**
M/B	0.000	0.348		0.001	0.014	**	0.001	0.289		0.000	0.627	
$Ferror^+$ *x M/B*	0.153	0.371		0.337	0.125		-0.275	0.519		-0.648	0.079	*
$Ferror^-$ *x M/B*	0.088	0.624		0.367	0.016	**	0.578	0.087	*	0.052	0.842	
Size	-0.000	0.383		-0.000	0.739		0.002	0.168		-0.001	0.320	
σ*AF*	-0.017	0.371		-0.009	0.610		-0.021	0.549		0.004	0.918	
Mom	0.017	0.205		-0.010	0.457		0.008	0.771		-0.056	0.035	**
Leverage	0.004	0.370		0.007	0.068	*	-0.005	0.640		0.023	0.009	***
Number of observations	6,310			7,285			6,310			7,285		
Adjusted R^2	0.113			0.062			0.005			0.006		

Note: Please see Appendix B for variable definitions, *** p<0.010, ** p<0.050, * p<0.10

Table 7 Panel A
Robustness to the inclusion of alternative sources of online information

	(1) *CAR*			(2) *CAR*			(3) *CAR*		
	coef	p-value		coef	p-value		coef	p-value	
Intercept	-0.008	0.291		0.000	0.978		-0.009	0.282	
$Ferror^{+}$	1.334	0.147		1.557	0.000	***	2.392	0.002	***
$Ferror^{-}$	1.587	0.014	**	0.921	0.007	***	1.104	0.237	
HiAct	-0.000	0.910		-0.001	0.628		0.000	0.963	
$Ferror^{+}$ *x HiAct*	4.229	0.000	***	4.225	0.000	***	3.905	0.001	***
$Ferror^{-}$ *x HiAct*	2.813	0.011	**	0.665	0.325		1.211	0.310	
LoAct	-0.000	0.769		0.000	0.026	**	0.000	0.986	
$Ferror^{+}$ *x LoAct*	1.180	0.002	***	0.355	0.043	**	1.345	0.001	***
$Ferror^{-}$ *x LoAct*	-0.004	0.991		0.315	0.082	*	0.044	0.893	
M/B	-0.001	0.800		-0.001	0.534		-0.000	0.929	
$Ferror^{+}$ *x M/B*	1.069	0.411		0.826	0.198		0.515	0.697	
$Ferror^{-}$ *x M/B*	1.112	0.295		0.638	0.088	*	1.767	0.151	
Pre-AbSearch	0.006	0.120					0.004	0.305	
$Ferror^{+}$ *x Pre-AbSearch*	1.217	0.210					1.988	0.122	
$Ferror^{-}$ *x Pre-AbSearch*	-0.281	0.862					-1.205	0.453	
HiDJN				0.001	0.762		0.001	0.776	
$Ferror^{+}$ *x HiDJN*				0.380	0.631		-1.523	0.192	
$Ferror^{-}$ *x HiDJN*				2.092	0.001	***	1.676	0.175	
HiBlog				-0.003	0.312		-0.003	0.518	
$Ferror^{+}$ *x HiBlog*				1.268	0.184		0.764	0.552	
$Ferror^{-}$ *x HiBlog*				-0.618	0.461		1.075	0.396	
Size	0.001	0.440		-0.000	0.305		0.001	0.492	
sAF	-0.047	0.073	*	-0.009	0.547		-0.040	0.124	
Mom	-0.055	0.014	**	0.000	0.990		-0.055	0.016	**
Leverage	-0.000	0.992		0.004	0.255		-0.002	0.825	
Number of observations	2,866			13,266			2,687		
Adjusted R^2	0.083			0.083			0.096		

(Table 7 continued on the following page)

Table 7 Panel B
Robustness to the inclusion of alternative sources of online information

	(1) *PEAD*			(2) *PEAD*			(3) *PEAD*		
	coef	**p-value**		**coef**	**p-value**		**coef**	**p-value**	
Intercept	-0.020	0.145		0.006	0.454		-0.019	0.187	
Ferror^{+}	-0.173	0.872		0.808	0.122		-1.534	0.197	
Ferror^{-}	-0.483	0.685		-1.131	0.072	*	-0.870	0.649	
HiAct	-0.014	0.037	**	-0.006	0.070	*	-0.008	0.275	
Ferror^{+} *x HiAct*	-0.656	0.785		-0.086	0.935		-1.370	0.557	
Ferror^{-} *x HiAct*	-0.624	0.808		-0.051	0.964		2.297	0.377	
LoAct	-0.003	0.006	***	0.001	0.197		-0.002	0.026	**
Ferror^{+} *x LoAct*	0.353	0.581		-0.308	0.283		1.060	0.064	*
Ferror^{-} *x LoAct*	0.356	0.651		0.235	0.520		0.445	0.577	
M/B	-0.015	0.046	**	0.003	0.398		-0.014	0.074	*
Ferror^{+} *x M/B*	3.853	0.003	***	1.206	0.111		4.874	0.000	***
Ferror^{-} *x M/B*	1.803	0.408		2.710	0.003	***	1.214	0.638	
Pre-AbSearch	0.004	0.716					0.010	0.224	
Ferror^{+} *x Pre-AbSearch*	0.367	0.932					-3.596	0.230	
Ferror^{-} *x Pre-AbSearch*	3.994	0.376					7.461	0.092	*
HiDJN				0.001	0.806		-0.006	0.361	
Ferror^{+} *x HiDJN*				0.405	0.679		-0.330	0.777	
Ferror^{-} *x HiDJN*				1.283	0.193		-0.076	0.972	
HiBlog				-0.001	0.772		-0.011	0.125	
Ferror^{+} *x HiBlog*				1.130	0.311		3.793	0.046	**
Ferror^{-} *x HiBlog*				-2.955	0.055	*	-3.656	0.301	
Size	0.003	0.090	*	-0.001	0.517		0.003	0.108	
sAF	0.110	0.050	*	-0.001	0.982		0.091	0.119	
Mom	-0.033	0.456		-0.029	0.131		-0.022	0.611	
Leverage	0.059	0.000	***	0.015	0.028	**	0.065	0.000	***
Number of observations	2,866			13,266			2,687		
Adjusted R^2	0.024			0.005			0.028		

Note: Please see Appendix B for variable definitions, *** p<0.010, ** p<0.050, * p<0.10